

# Rapid Nonlinear Topology Optimization using Precomputed Reduced-Order Models

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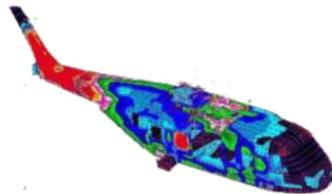
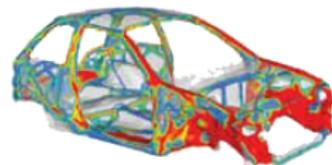
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# Motivation

- For industry-scale design problems, topology optimization is a beneficial tool that is *time and resource intensive*
  - Large number of calls to structural solver usually required
  - Each structural call is expensive, especially for nonlinear 3D High-Dimensional Models (HDM)
- Use a Reduced-Order Model (ROM) as a surrogate for the structural model in a material topology optimization loop
  - Large speedups over HDM realized



## 0-1 Material Topology Optimization

$$\begin{aligned} & \underset{\boldsymbol{\chi} \in \mathbb{R}^{n_{el}}}{\text{minimize}} && \mathcal{L}(\mathbf{u}(\boldsymbol{\chi}), \boldsymbol{\chi}) \\ & \text{subject to} && \mathbf{c}(\mathbf{u}(\boldsymbol{\chi}), \boldsymbol{\chi}) \leq 0 \end{aligned}$$

- $\mathbf{u}$  (structural displacements) is implicitly defined as a function of  $\boldsymbol{\chi}$  through the HDM equation

$$\mathbf{f}^{int}(\mathbf{u}) = \mathbf{f}^{ext}$$

$$\mathbb{C}^e = \mathbb{C}_0^e \boldsymbol{\chi}_e \quad \rho^e = \rho_0^e \boldsymbol{\chi}_e \quad \boldsymbol{\chi}_e = \begin{cases} 0, & e \notin \Omega^* \\ 1, & e \in \Omega^* \end{cases}$$

- General nonlinear setting considered (geometric and material nonlinearities)



## Reduced-Order Model

- Model Order Reduction (MOR) assumption
  - State vector lies in low-dimensional subspace defined by a Reduced-Order Basis (ROB)  $\Phi \in \mathbb{R}^{N \times k_u}$

$$\mathbf{u} \approx \Phi \mathbf{y}$$

- $k_u \ll N$
- $N$  equations,  $k_u$  unknowns

$$\mathbf{f}^{int}(\Phi \mathbf{y}) = \mathbf{f}^{ext}$$

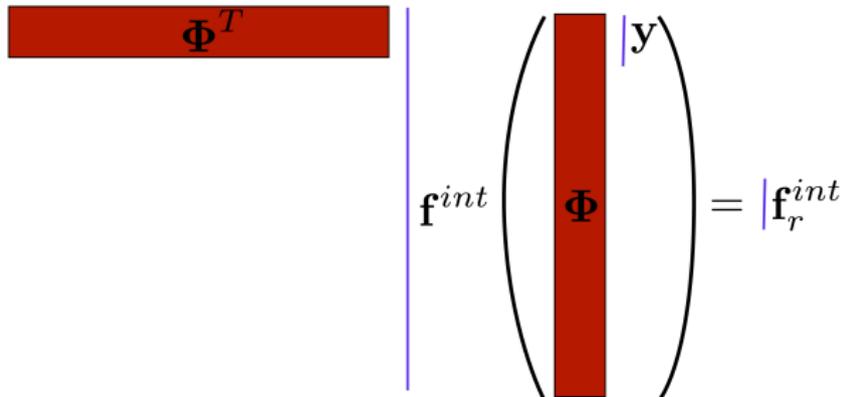
- Galerkin projection

$$\Phi^T \mathbf{f}^{int}(\Phi \mathbf{y}) = \Phi^T \mathbf{f}^{ext}$$



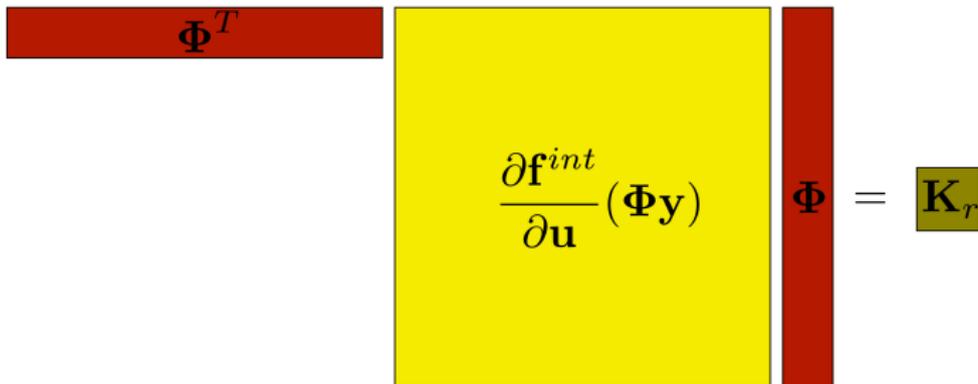
## NL ROM Bottleneck - Internal Force

$$\Phi^T \mathbf{f}^{int}(\Phi \mathbf{y}) = \Phi^T \mathbf{f}^{ext}$$



# NL ROM Bottleneck - Tangent Stiffness

$$\Phi^T \mathbf{f}^{int}(\Phi \mathbf{y}) = \Phi^T \mathbf{f}^{ext}$$



## Approximation of reduced internal force, $\Phi^T \mathbf{f}^{\text{int}}(\Phi \mathbf{y})$

- For general nonlinear problems, high-dimensional quantities cannot be precomputed since they change at every iteration
- For *polynomial* nonlinearities, there is an opportunity for precomputation
- Approach
  - Approximate  $\mathbf{f}^r = \Phi^T \mathbf{f}^{\text{int}}(\Phi \mathbf{y})$  by polynomial via Taylor series
    - We choose a third-order series
    - Exact representation of reduced internal force for *St. Venant-Kirchhoff* materials
  - Precompute coefficient tensors
  - Online operations will only involve *small* quantities
    - Remove online bottleneck
    - Pay price in offline phase



## Taylor Series of $\Phi^T \mathbf{f}^{\text{int}}(\Phi \mathbf{y})$

Consider Taylor series expansion of  $\mathbf{f}^r(\mathbf{y}) = \Phi^T \mathbf{f}^{\text{int}}(\Phi \mathbf{y})$  about  $\bar{\mathbf{y}}$

$$\begin{aligned} \mathbf{f}_i^r(\mathbf{y}) &\approx \mathbf{f}_i^r(\bar{\mathbf{y}}) + \frac{\partial \mathbf{f}_i^r}{\partial \mathbf{y}_j}(\bar{\mathbf{y}}) \cdot (\mathbf{y} - \bar{\mathbf{y}})_j \\ &\quad + \frac{1}{2} \frac{\partial^2 \mathbf{f}_i^r}{\partial \mathbf{y}_j \partial \mathbf{y}_k}(\bar{\mathbf{y}}) \cdot (\mathbf{y} - \bar{\mathbf{y}})_j (\mathbf{y} - \bar{\mathbf{y}})_k \\ &\quad + \frac{1}{6} \frac{\partial^3 \mathbf{f}_i^r}{\partial \mathbf{y}_j \partial \mathbf{y}_k \partial \mathbf{y}_l}(\bar{\mathbf{y}}) \cdot (\mathbf{y} - \bar{\mathbf{y}})_j (\mathbf{y} - \bar{\mathbf{y}})_k (\mathbf{y} - \bar{\mathbf{y}})_l \end{aligned}$$



## Reduced Derivatives

- Reduced derivatives computable by:
  - Projection of *full* order derivatives
  - Directly via finite differences

$$\alpha_i = \mathbf{f}_i^r(\bar{\mathbf{y}}) = \Phi_{pi} \mathbf{f}_p^{\text{int}}(\Phi \bar{\mathbf{y}})$$

$$\beta_{ij} = \frac{\partial \mathbf{f}_i^r}{\partial \mathbf{y}_j}(\bar{\mathbf{y}}) = \Phi_{pi} \Phi_{qj} \frac{\partial \mathbf{f}_p^{\text{int}}}{\partial \mathbf{u}_q}(\Phi \bar{\mathbf{y}})$$

$$\gamma_{ijk} = \frac{\partial^2 \mathbf{f}_i^r}{\partial \mathbf{y}_j \partial \mathbf{y}_k}(\bar{\mathbf{y}}) = \Phi_{pi} \Phi_{qj} \Phi_{rk} \frac{\partial^2 \mathbf{f}_p^{\text{int}}}{\partial \mathbf{u}_q \partial \mathbf{u}_r}(\Phi \bar{\mathbf{y}})$$

$$\omega_{ijkl} = \frac{\partial^3 \mathbf{f}_i^r}{\partial \mathbf{y}_j \partial \mathbf{y}_k \partial \mathbf{y}_l}(\bar{\mathbf{y}}) = \Phi_{pi} \Phi_{qj} \Phi_{rk} \Phi_{sl} \frac{\partial^3 \mathbf{f}_p^{\text{int}}}{\partial \mathbf{u}_q \partial \mathbf{u}_r \partial \mathbf{u}_s}(\Phi \bar{\mathbf{y}})$$



## Reduced internal force

Reduced internal force becomes

$$\begin{aligned} \mathbf{f}_i^r(\mathbf{y}) = & \alpha_i + \beta_{ij}(\mathbf{y} - \bar{\mathbf{y}})_j \\ & + \frac{1}{2}\gamma_{ijk}(\mathbf{y} - \bar{\mathbf{y}})_j(\mathbf{y} - \bar{\mathbf{y}})_k \\ & + \frac{1}{6}\omega_{ijkl}(\mathbf{y} - \bar{\mathbf{y}})_j(\mathbf{y} - \bar{\mathbf{y}})_k(\mathbf{y} - \bar{\mathbf{y}})_l, \end{aligned}$$

which only depends on quantities scaling with the *reduced* dimension.



## Reduced internal force - material dependence

- As written, the material properties for a given material are *baked into* the polynomial coefficients
- For notational simplicity, we consider two material parameters:  $\rho$  (density) and  $\eta$

$$\boldsymbol{\alpha} = \boldsymbol{\alpha}(\rho, \eta)$$

$$\boldsymbol{\beta} = \boldsymbol{\beta}(\rho, \eta)$$

$$\boldsymbol{\gamma} = \boldsymbol{\gamma}(\rho, \eta)$$

$$\boldsymbol{\omega} = \boldsymbol{\omega}(\rho, \eta)$$

- In the context of 0-1 topology optimization,  $\boldsymbol{\alpha}, \boldsymbol{\beta}, \boldsymbol{\gamma}, \boldsymbol{\omega}$  need to be recomputed at each new distribution of  $\rho, \eta$ 
  - Extremely expensive – destroy all speedup potential



## Material Representation

- Recall the material parameters are *spatial distributions*, i.e.  
 $\rho = \rho(\mathbf{X})$  and  $\eta = \eta(\mathbf{X})$
- Define admissible distributions:  $\{\phi_i^\rho\}_{i=1}^n, \{\phi_i^\eta\}_{i=1}^n$ 
  - Require

$$\rho(\mathbf{X}) = \phi_i^\rho(\mathbf{X})\xi_i$$

$$\eta(\mathbf{X}) = \phi_i^\eta(\mathbf{X})\xi_i$$

- Many possible choices admissible distributions
  - Here, collected via *configuration snapshots*



## Reduced internal force - material dependence

- Suppose the coefficient matrices depend *linearly* on material parameters
  - Can be accomplished by carefully choosing parameters (i.e.  $\lambda, \mu$  instead of  $E, \nu$ ) or linearization via Taylor series
- Use material assumptions in reduced internal force

$$\begin{aligned}
 \mathbf{f}_i^r(\mathbf{y}) = & \sum_a \alpha_i(\phi_a^\rho, \phi_a^\eta) \xi_a \\
 & + \sum_a \beta_{ij}(\phi_a^\rho, \phi_a^\eta) \xi_a (\mathbf{y} - \bar{\mathbf{y}})_j \\
 & + \frac{1}{2} \sum_a \gamma_{ijk}(\phi_a^\rho, \phi_a^\eta) \xi_a (\mathbf{y} - \bar{\mathbf{y}})_j (\mathbf{y} - \bar{\mathbf{y}})_k \\
 & + \frac{1}{6} \sum_a \omega_{ijkl}(\phi_a^\rho, \phi_a^\eta) \xi_a (\mathbf{y} - \bar{\mathbf{y}})_j (\mathbf{y} - \bar{\mathbf{y}})_k (\mathbf{y} - \bar{\mathbf{y}})_l
 \end{aligned}$$

- Quantities in blue can be precomputed offline



## ROM Pre-computation Approach

$$\Phi^T \mathbf{f}^{int}(\Phi \mathbf{y}) = \Phi^T \mathbf{f}^{ext}$$

### Advantages

- Only need to solve small, cubic nonlinear system online
- Large speedups possible without hyperreduction,  $\mathcal{O}(10^2)$
- Amenable to 0-1 material topology optimization

### Disadvantages

- Offline cost scales as  $\mathcal{O}(n_\alpha \cdot n_{el} \cdot k_{\mathbf{u}}^4)$
- Offline storage scales as  $\mathcal{O}(n_\alpha \cdot k_{\mathbf{u}}^4)$
- Online storage scales as  $\mathcal{O}(k_{\mathbf{u}}^4)$
- Can only vary material distribution in the subspace defined by the material snapshot vectors



# Reduced Topology Optimization

$$\begin{aligned} & \underset{\boldsymbol{\xi} \in \mathbb{R}^n}{\text{minimize}} && \hat{\mathcal{L}}(\mathbf{y}(\boldsymbol{\xi}), \boldsymbol{\xi}) \\ & \text{subject to} && \hat{\mathbf{c}}(\mathbf{y}(\boldsymbol{\xi}), \boldsymbol{\xi}) \leq 0 \end{aligned}$$

- $\mathbf{y}$  is implicitly defined as a function of  $\boldsymbol{\xi}$  through the ROM equation

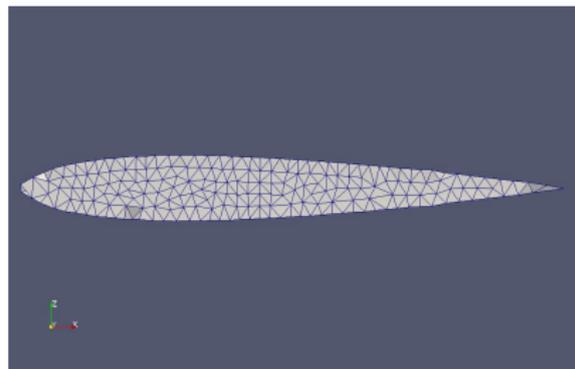
$$\boldsymbol{\Phi}^T \mathbf{f}^{int}(\boldsymbol{\Phi} \mathbf{y}) = \boldsymbol{\Phi}^T \mathbf{f}^{ext}$$

which can be computed efficiently



## Problem Setup

- Neo-Hookean material
- 90,799 tetrahedral elements
- 29,252 nodes, 86,493 dof
- Static simulation with load applied in 10 increments
- Loads: Bending (X- and Y- axis), Twisting, Self-Weight
- ROM size:  $k_{\mathbf{u}} = 5$

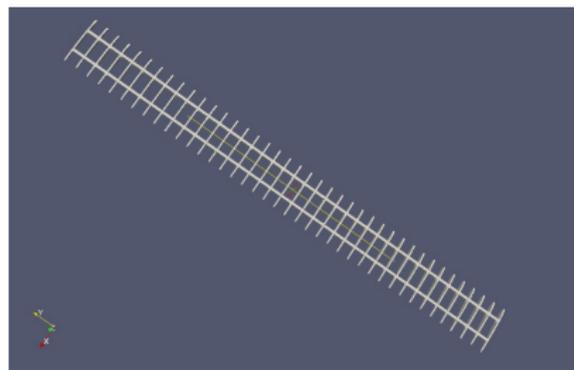


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40 Ribs



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## Simulation Results

- Single static simulation
- Training for ROMs: single static simulation (with load stepping) with *all* ribs
- Reproductive simulation

	Offline (s)	Online (s)	Speedup	Error (%)
HDM	-	674	-	-
ROM	0.988	412	1.64	0.002
ROM-precomp	6,724	1.19	<b>566</b>	5.54



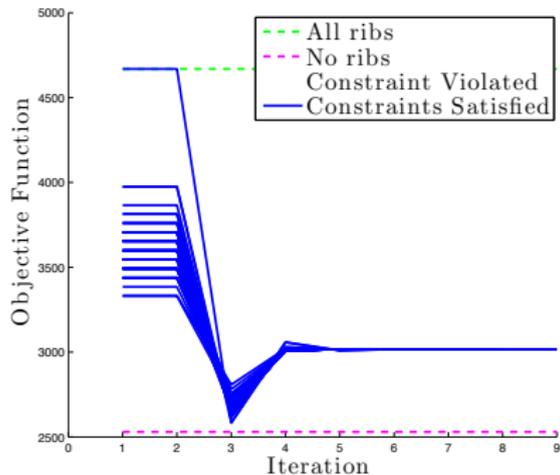
# Optimization Setup

- Minimize structural weight
- Constraint on maximum vertical horizontal displacements
- 41 Material Snapshots
  - 40 possible ribs
  - two spars jointly

Material Snapshots



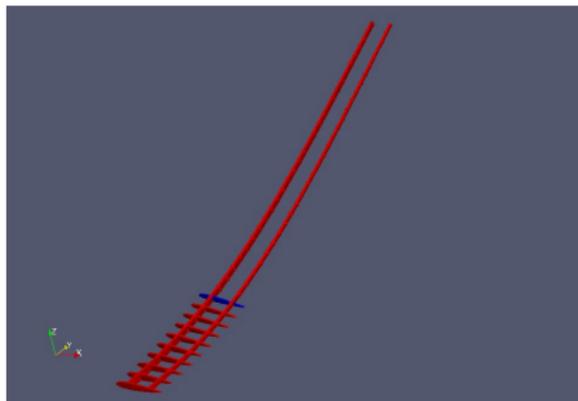
# Optimization Results



Optimization Iterates



# Optimization Results



Deformed Configuration (Optimal Solution)

	Initial Guess	Optimal Solution
Structural Weight	$4.67 \times 10^3$	$3.02 \times 10^3$
Constraint Violation	0	$7.10 \times 10^{-23}$



## Conclusion and Future Work

- New method for material topology optimization using reduced-order models
  - Applicable in nonlinear setting
  - $\mathcal{O}(10^2)$  speedup over HDM
- Strongly enforce manufacturability constraints
  - selection of material snapshots
- Address large problems
- Investigate extending method to more sophisticated topology optimization techniques

